A spatiotemporal approach for detecting street intersections

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Abstract

The purpose of this research is to propose and test a method for detecting street junctions using crowdsourced data from vehicles in form of gps data. Core of the method is the detection of low-speed sequences, as speed is expected to be so at such locations, and the clustering of representative points of such sequences using a spatiotemporal approach. We present the results of the method by testing it on an open dataset.

1 Introduction

Without doubt GPS technologies have played an important role of how mobility and transportation have been shaped nowadays and maps being the core components of such systems need to be up-to-date regarding the topological and topographical features of the road network. Many different approaches have been proposed for automating the map construction process (Cao and Krumm, 2009; Karagiorgou and Pfoser, 2012; Biagioni and Eriksson, 2012) and their resulting precision depends very much on the quality of the extracted junction locations, used as connecting nodes of the automatically constructed roads. In the following section we propose a new method for detecting junctions by clustering locations where low-speed patterns in vehicle trajectories are observed. The main difference from existing methods (Fathi and Krumm, 2010, Wu et al. 2013), is that it counts on vehicles speed and not on turning points along vehicle trajectories.

2 Method

For testing the method we used a publicly available dataset (Figure 1, http://mapconstruction.org/). In the first step (Figure 2), we detect low speed sequences of vehicles by using the CB-SMoT spatiotemporal clustering (Palma et al. 2008). To our knowledge this algorithm has been used so far only for finding interesting places by regulating the minimum amount of time that a moving object stays within an area. For each low speed sequence, we select a representative point with the lowest speed criterion (Figure 3). The two parameters were selected experimentally (Eps =20m, minTime=5sec). Then, we cluster the representative points of all trajectories using the density-based clustering algorithm DB-SCAN, where low speed events that are spatially closed are grouped in the same cluster (Figure 4). Junction centers are predicted at a final step (Figure 6), where clusters' headings as well as spatial reasoning criteria (Figure 5) regarding the presence of nearby clusters are taken into account (Zourlidou and Sester, 2016).

Figure 1: Data in the area of study.

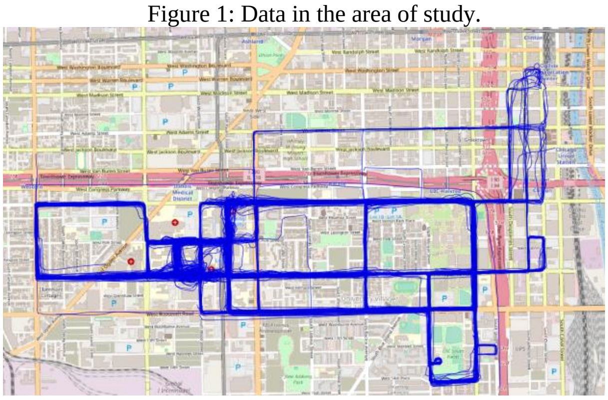
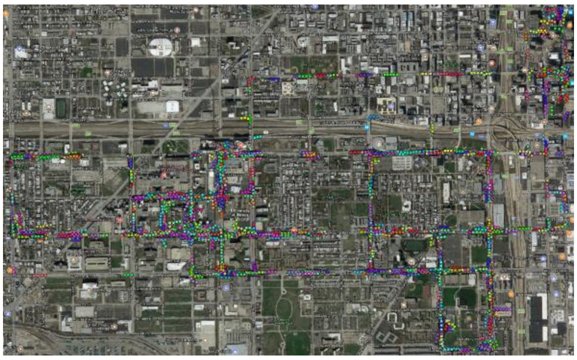


Figure 2: Results of the CB-SMoT algorithm with Eps = 20 and minTime = 5.



3 Results

We constructed the groundtruth map by mining the junction centers from Openstreetmap. Then, we computed the distance between predicted junction locations and groundtruth locations. For the 69 predicted junction locations, the average error estimated as the sum of the distances between groundtruth and predicted locations divided by the number of junctions. The average error was found 12.35m, by using the folllowing parameters: CB-SMoT: Eps = 20, minTime = 5,DBSCAN: Eps = 15, minSamples = 5. We plan to test the method to different datasets in different cities for examining how the parameter are affected, as well as to compute the confusion matrix of the predicted classes/actual classes.

Figure 3: Representatives points of the stop sequences in Figure 2.

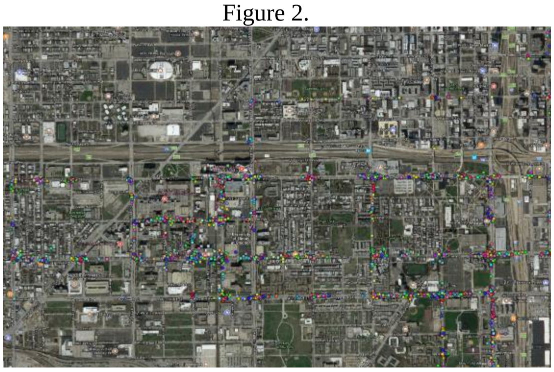


Figure 4: DBSCAN results for Eps=15 and nSamples=5, applied on results depicted in Figure 3.

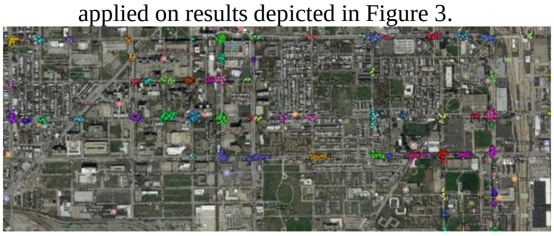


Figure 5: Cluster of stops with direction west (blue) and south (orange). The predicted junction center found as the intersection of two straight lines (red).

Figure 6: The predicted intersection centers.

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